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Emerging Markets Queries in Finance and Business

Modeling S&P Bombay Stock Exchange BANKEX Index Volatility Patterns Using GARCH Model

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Abstract

The main objective of this article is to model the volatility patterns of the S&P Bombay Stock Exchange (BSE) BANKEX index which is the indian banking sector index. Currently, the Indian banking sector is one of fastest growing sector and all major banks have been included in S&P BANKEX index. The financial econometric approach includes GARCH (1, 1) model which is performed in order to capture asymmetric volatility clustering and leptokurtosis. Data time lag is considered from the first transaction day of January 2002 to last transaction day of June 2014. Empirical outcomes suggest that volatility shocks in series and volatility clusters. The volatility impact has generated highly positive clockwise and resulted on actual stocks. Moreover, the empirical findings reveal that the BANKEX index grown over 17 times in 12 years and volatility returns have been found present in listed stocks.

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1. Introduction

In recent past, stock market volatility modeling and estimation have established certain issues of great interest not only for investors, financial practitioners and academics, especially in terms of modern finance perspectives. Moreover, one of the main aim of investment process is to reduce the high exposure to risk considering the fact that international portfolio diversification provides superior risk-adjusted returns. In this sense, globalization and financial liberalization have significantly contributed to the accuracy of the investment process. However, on a deeper level, certain global factors such as economic, historical, political, social, demographic and cultural have a critical influence on the investment framework.

Financial modeling highlights the fact that stock price movements exhibit certain stylized facts such as volatility clustering (Mandelbrot, 1963), financial leverage effects (Black, 1976), leptokurtosis, heavy tailed distribution, conditional heteroskedasticity, asymmetric volatility effects, unconditional time-varying moments and severe deviations from normality in the context of extreme events. According to the most recent official raport of FTSE Country Classification issued on September 2013, following subcategories are included, i.e.: developed, advanced emerging, secondary emerging and frontier. India is included in the category of secondary emerging countries. The financial benefits and investment opportunities provided by international portfolio diversification strategies are very attractive in terms of Bombay Stock Exchange.

2. Literature review

Bollerslev (1986) has generalized ARCH model by including lagged valued of the conditional variance. The GARCH model allows a wider range of behavior and patterns especially in the case of more persistent volatility. The most general form of the model is GARCH (1,1) where GARCH stands for Generalized Autoregressive Conditional Heteroscedasticity. Moreover, a GARCH model or basically or Generalized ARCH model represents an extension of the ARCH model which otherwise is very similar to an ARMA model. According to Brooks (1996) such a generalization of ARCH model, namely GARCH model can be perceived as an infinite order ARCH model. Engle (1982) argued that traditional econometric models assume a constant one-period forecast variance and therefore in order to generalize this implausible assumption, it was implemented a new class of stochastic processes called autoregressive conditional heteroscedastic (ARCH) processes. On the other hand, Brooks (1996) suggested that it is highly unlikely that a GARCH model of order greater than one in the autoregressive and moving average components would be required, since by definition, a GARCH (1,1) model implies an infinitely long memory with respect to past news , ie innovations.

Prasanna and Menon (2013) suggested that the global process of financial integration between Indian stock market and international stock markets caused the absorption domestic and global news into the asset prices and stock indices. Trivedi (2013) argued that generally the banking sector in India was distinguished by accuracy and high confidence even in dramatic periods caused by extreme events such as the global financial crisis. Nateson et al. (2013) investigated spillover effect of volatility in Indian BSE Sensex on BSE sectoral indices based on GARCH (1,1) model. The authors emphasized the importance of financial integration due to volatility transmission patterns especially in terms of risk management strategies and portfolio diversification for all investment sectors in India. Moreover, Basabi, Roy and Niyogi (2009) examined conditional volatility patterns of the BSE BANKEX index based on symmetric and asymmetric GARCH models. The authors revealed the existence of leverage effect considering the response to positive and negative news (innovations).

3. Methodological approach and empirical results

The financial data series consists of daily closing asset prices for the selected stock index during the period between January 2002 and June 2014 with the exception of legal holidays or other events when stock markets haven't performed transactions. The continuously-compounded daily returns are calculated using the log-difference of the closing prices of stock market selected index, i.e. S&P Bombay Stock Exchange (BSE) BANKEX as follows:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) = \ln(P_t) - \ln(P_{t-1}) \tag{1}$$

Where R_t represents daily returns of indices and P_t stands for daily closing prices of sample index.

Generalized autoregressive modeling known as GARCH has became one of the popular methods to estimate financial market volatility. GARCH (1, 1) model was developed by Bollerslev and Taylor (1986). This model allows conditional variance of all variables to be dependent upon previous legs and it reflects on entire series. However the first lag of squared residual will be from mean equation and this presents idea about volatility from the previous time periods. General most used model for formulate GARCH (1, 1) as follows:

$$h_t = \omega + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1} \tag{2}$$

We need to follow hypothesis of covariance stationary as unconditional variance and to exist that it processed by following;

$$\sigma^2 = Var(u_t) = E(u_t^2) = E(\omega + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1}) \tag{3}$$

$$\sigma^2 = Error! \tag{4}$$

We form GARCH (1, 1) conditional variance equation Var (u_t | h_{t-1}) = E(u_t^2| h_{t-1}) = h_t , and thus it can simply take the following form, ie : $h_t = \omega + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1}$.

Hence the final formulation will take form of $h_t = \omega + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1}$ based on both ARCH term and GARCH term.

The implementation of GARCH model limits the stationarity of the data and presence of ARCH effect in time series of BANKEX index. However, we test the results by using ADF test called as Augment Dickey-Fuller test (ADF test) which represents unit root problems under hypothesis Ho=p_0 and p_1. Generally all time series has unit root problems and it must be filtered and allowed for ARCH processes. For this purpose we have allowed trend for all indices by adding intercept to the model y_t (or Δy_t) on 1, y_{t-1}, Δy_{t-1},…, Δy_{t-p+1}, computing the t-statistic which will have the following expression, by comparing its value to percentiles of DF τ_μ distribution :

$$\tau_t = \frac{\hat{\rho} - 1}{se(\hat{\rho})} \tag{5}$$

It has produced higher negative value than its critical value at 1%, 5% and 10% level which allows series for ARCH and proves no unit root problems. This is well enough to process for GARCH (1, 1) model to estimate volatility of BANKEX index. The first step in the empirical analysis process is to evaluate the basic statistics data series, such as following features : Mean : 000.0918151, Median : 0.00123011, Min : -0.144804, Max : 0.175483, Std. Dev. : 0.0201306, Skewness : -0.0579478 and Ex. Kurtosis : 5.67762. This basic statistics represent summary of statistics of BANKEX index from January 2002 to June 2014 as it can be distinguished in the figure below:

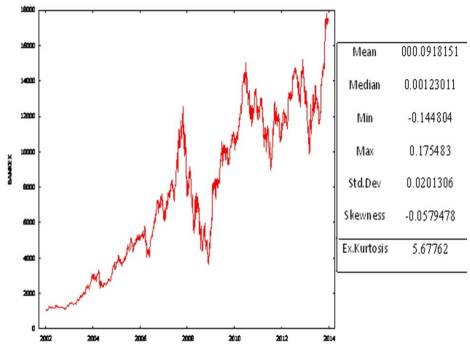

Fig.1 Descriptive statistics and the trend of S&P BSE BANKEX index (individual chart)
Source: Author's own computations based on selected financial data series

BANKEX index represents banking stock moments listed on Bombay Stock Exchange and the Fig1 represents the historical graph of BANKEX moments from year 2002 to 2014 (see Fig1). The mean value near to zero followed by median, a large difference is visible from Min value to Max value of the BANKEX index through all these years. The standard deviations figures are comparatively important since that explores the degree of risks and returns which represents 0.0201 (of the log first difference values) and negative skewness and exceeding value of Kurtosis by 2.67 (5.67). The S&P BSE BANKEX index reveals upperside strong moment of stocks from January 2002 to June 2014 with visible downfall between the years 2008-2009 and strong recovery of banking sector after global financial crisis. The stock index journey started with base point i.e. 1000 points on Jan 01, 2002 and reached to 17475 at last day of trading in covered study period. It shows the journey growth of 17 times of the base index in 12 years including financial recession.

This fundamental maths suggests strong banking fundamentals in India which includes major public sector banks.

The original data has be converted to log returns for all years. We used 3122 daily observations as data from Jan 2002 to June 2014. The first log difference is considered and ADF test (KPSS) test has been tested. The ADF test statistics results are significant at degree of 1%, 5% and 10% level. Fig2 represents the stationary data outcome and ADF test statistics results.

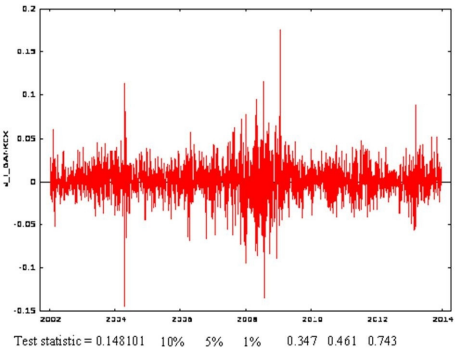

Fig.2 Log returns series of S&P BSE BANKEX index (individual chart)
Source: Author's own computations based on selected financial data series

The long sketches are visible (see fig. 2) clearly in year 2004, 2007, 2008 and 2009. These long sketches moments are not casual and represents abnormal market behavior. Nevertheless the international global financial crisis are clearly visible in the market history. Negative skewness and higher kurtosis creates leptokurtosis impact which makes long tail (see fig3). The banking sector index of Bombay Stock exchange suggests lowest pick level in year 2004 and measurable highest up level sketches in year 2009. The other small and medium size sketches resulted from standard volatility of BANKEX. Augment Dickey-Fuller test (ADF test) provides significance of BANKEX index at level of 1%, 5% and 10%. We consider significance at level of 5%.

Furthermore the negative skewness and higher kurtosis created long tail (see Fig3) which mentioned by Q-Q ploting of BANKEX index. The degree of negative skewness and higher kurtosis has lasted the tail from level of -0.15 degree to over +0.15 degree visible in Fig. 3.

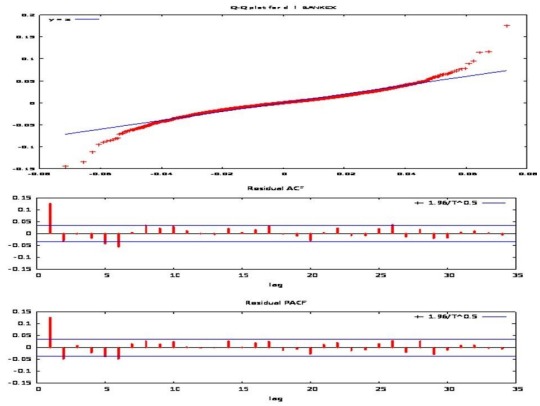

Fig. 3 The Q-Q plot, Residual ACF and Residual PACF for of S&P BSE BANKEX index
Source: Author's own computations based on selected financial data series

We can see the ACF and PACF pattern which represents mild negative autocorrelations in BANKEX time series. These patterns are collected from GARCH model output which represents strong positive autocorrelations (see fig3). The ACF and PACF patters also represent strong stationary series and presence of

AR term in financial series of BANKEX. Generalized autoregressive modeling can be now proceeded to estimate the volatility in the series. We employ here GARCH model with (1) Garch term and (1) Arch term, called as GARCH (1, 1).

The GARCH (1, 1) model can be formulated in the following estimation:

$$h_t = \omega + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1} \text{ and results } (\alpha_1) + (\beta_1) = 0.0825931 + 0.901536 = 0.9841291 < 1$$

What we can see in the above explored formulation is the sum of ARCH term and GARCH term which must be less than 1 (ie <1) and this hypothesis is proved in the previous expression. This issue highlights a strong presence of volatility in the financial series of BANKEX and the GARCH (1, 1) model is fitted perfectly in the financial series. The calculative answers does not disclosed in paper which found highly significant in terms of final answer. First log difference considered as input data for the formulation of Bollerslev GARCH (1, 1) model. Financial investments in BANKEX series have the risk value of 0.2013 degree where as the series volatility 0.9841291, that is very similar to 1 and proves high degree of changes at upper side (positive shocks) and lower side (negative shocks). The return ratios and the index growth i.e. 1000 to over 17000 represent the great investor interest in the BANKEX stocks. Nevertheless the stock is capable to recover from great negative shocks or even from global financial crisis as that has evident to fast recovery.

4. Conclusions

The major objective of this research paper is to investigate the behavior of S&P Bombay Stock Exchange (BSE) BANKEX Index volatility patterns using GARCH model. A S&P BSE BANKEX index moment of last 12 years represents also the great attractions of investors and the high volume of turnovers. Bollerslev GARCH (1, 1) model fitted well on BANKEX financial series. Nevertheless, the actual difference between Min and Max reveals high degree of volatility in Bombay Stock Exchange for open ended stocks. We considered data ranging from 1st Jan 2002 to last day of June 2014. Basic statistics shows the mean and risk value in the BANKEX index (0.2013). The returns are over 17 times in 12 years and BANKEX index have absorbed the global financial crisis well. The stock fluctuations are abnormal and highly volatile since the evidence presence in year 2004 for down effect shocks and 2009 for positive shocks. ACF and PACF shows less degree of negative patterns and more positive patterns and presence of AR effect in series.

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